Do Investors Herd in Cryptocurrencies – and why?

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Abstract

We investigate herding and its possible determinants in the cryptocurrency market for the December 2013 – July 2018 period. Herding is significant (irrespective of Bitcoin's presence and trends over time) and strongly asymmetric (appearing stronger during up-markets, low volatility and high volume days), with smaller cryptocurrencies enhancing its magnitude. Our findings suggest that the cryptocurrency market entails strong destabilizing potential, the latter being of particular relevance to the authorities entrusted with its regulatory treatment.

JEL classification: G40, G15, C58, C22

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1. Introduction

Herding as a trading practice constitutes, perhaps, the most widely established facet of investors' behavior in financial markets over the centuries. Historically, the earliest evidence on herding in organized capital markets hails from Joseph De La Vega's book "Confusion of Confusions" (Corzo et al., 2014), with Galbraith (1994) and Kindleberger and Aliber (2005) presenting an excellent overview of historical market episodes entailing herding among

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investors since the 17th century. Today, its presence has to date been confirmed, to varying degrees, internationally, for several asset classes, including equities, bonds, currencies, options, futures and REITs (Spyrou, 2013).

Herding arises when investors discard their private signals or fundamentals, choosing instead to align their decisions with those of the consensus following interactive observation (Hirshleifer and Teoh, 2003). Such behaviour has often been argued to be intentional, motivated by the anticipation of informational (Devenow and Welch, 1996) and reputational (Jiang and Verardo, 2018) payoffs; however, a number of factors, including commonality in the regulatory framework (Blake et al., 2017) and style investing (Choi and Sias, 2009) have been found to promote correlation in investors' trades without interactive observation being required, in effect giving rise to spurious herding. Liao et al. (2011) and Celiker et al. (2015) showed that market sentiment motivates herding at both the market and sector levels; Barber et al. (2009) reported significant correlations in the trades of retail investors, the prime candidates for noise trading (given their lower sophistication), driven mainly by their common susceptibility to behavioural biases. Blasco et al. (2012) and Economou et al. (2015) found stronger herding tendencies on days with high volatility; Arjoona and Bhatnagar (2017) reported significant herding in frontier markets, with more prominent evidence for smaller stocks; and Lux (1995) demonstrated how herd behaviour can foment bubbles in capital markets.

Recently, the Fourth Industrial Revolution has led to the proliferation of smart technologies globally, bringing forth ground-breaking changes in economic life. In that respect, the financial sector has witnessed the rise of cryptocurrencies, largely motivated by the decline in public trust toward the central banking system since the global crisis of 2008 (Weber, 2014). As of July 2018, there are more than two thousand cryptocurrencies with a total market capitalization of more than $211 billion (www.coinmarketcap.com). An investor purchasing one Bitcoin (the world's first-ever launched cryptocurrency) in July 2010 (at $0.08) would have found themselves enjoying a 243,716% return on 16th December, 2017 (at $19,497.40, Bitcoin's all-time peak). These phenomenal returns paved the way for the popularization of cryptocurrencies, fuelling Initial Coin Offerings and cryptocurrency-mining (Chester, 2017). Cryptocurrency trading has been increasingly attracting the attention of policymakers and the wider public (Pieters and Vivanco, 2017), particularly following the 2018 cryptocurrency crash[2]. Under this context, it is very important to investigate how herding, if present in this dramatically changing asset market, varies with its volatility and trading activity.

Empirical evidence indicates that cryptocurrencies are susceptible to market and media sentiments (Weber, 2014; Cheah and Fry, 2015), noise trading (Cheung et al., 2015; Fry and Cheah, 2016), high volatility (Phillip et al., 2018; Gkillas and Katsiampa, 2018; Blau, 2017), and speculative bubbles (Dowd, 2014; Cheah and Fry, 2015; Symitsi and Chalvatzis, in press). An interesting issue here is that the aforementioned factors have been found to be associated with herding among investors in equity markets. The fact that the evolution of cryptocurrencies has involved considerable peer-to-peer interaction among both coin-issuers and investors (Chester, 2017) and the evidence showing that cryptocurrencies lack fundamental value (Cheah and Fry, 2015) suggest that investors would deem herding a viable option when trading cryptocurrencies in order to tackle the uncertainty of this constantly evolving asset class. However, extant research on herding in the cryptocurrency market is at a relatively nascent stage. The limited evidence on cryptocurrency herding indicates that it is significant inter-temporally (Bouri et al., in press), taking place mainly during market slumps and being the result of smaller cryptocurrencies tracking their larger peers (Vidal-Tomás et al., in press).

[2] After an unprecedented rally of cryptocurrency prices in 2017, the bubble in cryptocurrency market burst in January 2018. Bitcoin, as the trigger of this crash, plunged almost 65 percent between 6 January and 6 February 2018 (www.coinmarketcap.com).

We contribute to this line of research by exploring herd behaviour in the cryptocurrency market using 296 cryptocurrencies, accounting for 98% of this asset market's capitalization, with our main focus being to assess whether performance, volatility, volume and size constitute key determinants of cryptocurrency herding. We present evidence denoting that cryptocurrency herding is significant, irrespective of Bitcoin's presence and trends over time. Our findings further suggest that cryptocurrency herding exhibits asymmetric properties, appearing consistently stronger during up markets, low volatility and high volume days. Equal-weighted herding is stronger than value-weighted herding, thus indicating that herding in the cryptocurrency market is strongly motivated by smaller cryptocurrencies, similar to the results presented by Vidal-Tomás et al. (in press).

Our study contributes significantly to the behavioral finance research on cryptocurrencies in several distinct ways. First, by covering a large portion of small capitalization cryptocurrencies (compared to previous herding studies, whose samples tended to focus on the largest cryptocurrencies only)[3], our research allows insight into the role of smaller cryptocurrencies in the herding dynamics of that asset class. Second, given that cryptocurrencies' performance, volatility and volume are associated with their market's significant price-swings, popular following and peer-to-peer interactions, studying how the presence of herding varies with these market variables allows us to gauge the extent to which this market's dynamics are related to herding.

The rest of this paper is organized as follows: Section 2 outlines our data and empirical design; Section 3 presents and discusses our results; Section 4 concludes.

[3] Compared to our sample of 296 cryptocurrencies, Bouri et al. (in press)'s sample included the 14 largest cryptocurrencies, whereas Vidal-Tomás et al. (in press) utilized a total of 65 cryptocurrencies.

2. Data and Methodology

Daily observations of price indices, market capitalization and volume of the top 296 cryptocurrencies (corresponding to 98% of the cryptocurrency market's capitalization as of July 11th, 2018) were obtained from www.coinmarketcap.com for the 27/12/2013 – 10/07/2018 window. The selection of 27/12/2013 as the start-date is motivated by the fact that volume-data are available from that date onward.

Our empirical design hinges on the measure proposed by Chang et al. (2000), which assesses the relationship between the cross-sectional returns' dispersion and absolute market returns. If there is no herding, this relationship is expected to be positive and linear, courtesy of securities' varying sensitivities to market movements. If herding is present during periods with extreme market movements, securities' returns will be expected to cluster around the average market return, leading to a reduction in the cross-sectional returns' dispersion; as a result, the aforementioned relationship will turn negative and (given the high absolute market returns accompanying extreme market movements) non-linear. Chang et al. (2000) test for this empirically via the following specification:

$$CSAD_t = a_0 + a_1 \left| R_{m,t} \right| + a_2 R_{m,t}^2 + u_t \tag{1}$$

In our paper's context, $R_{m,t}$ corresponds to the average return of all cryptocurrencies on day *t* and $CSAD_t$ is the daily cross-sectional absolute deviation, calculated as follows:

$$CSAD_t = \frac{\sum_{i=1}^{n} \left| R_{i,t} - R_{m,t} \right|}{n} \tag{2}$$

n is the number of traded cryptocurrencies on day *t* and $R_{i,t}$ is cryptocurrency *i*'s return on day *t*, calculated as the first logarithmic difference of its closing prices[4]. A significantly negative a_2 would denote the presence of herding.

[4] Following Urquhart (2018), we choose to use logarithmic returns rather than arithmetic returns to reduce skewness and kurtosis.

To assess whether herding varies across market states, we employ the following specifications:

$$CSAD_t = a_0 + a_1 D^{up}\left|R_{m,t}\right| + a_2(1 - D^{up})\left|R_{m,t}\right| + a_3 D^{up} R_{m,t}^2 + a_4(1 - D^{up})R_{m,t}^2 + u_t \quad (3)$$

$$CSAD_t = a_0 + a_1 D^{high-VT}\left|R_{m,t}\right| + a_2\left(1 - D^{high-VT}\right)\left|R_{m,t}\right| + a_3 D^{high-VT} R_{m,t}^2 + a_4\left(1 - D^{high-VT}\right)R_{m,t}^2 + u_t \quad (4)$$

$$CSAD_t = a_0 + a_1 D^{high-VL}\left|R_{m,t}\right| + a_2\left(1 - D^{high-VL}\right)\left|R_{m,t}\right| + a_3 D^{high-VL} R_{m,t}^2 + a_4\left(1 - D^{high-VL}\right)R_{m,t}^2 + u_t \quad (5)$$

Where:

D^{up} = 1 on up market days ($R_{m,t}$ > 0), zero otherwise;

$D^{high-VT}$= 1 on high volatility days, zero otherwise. Volatility is calculated as the squared value of $R_{m,t}$ and is considered to be high (low), if it is above (below) its 30-day moving average;

$D^{high-VL}$= 1 on high volume days, zero otherwise. Volume is considered to be high (low), if it is above (below) its 30-day moving average.

Significantly negative a_3 (a_4) values suggest that herding is significant during up (down) markets in Equation (3), on high (low) volatility days in Equation (4) and on high (low) volume days in Equation (5).

We further test whether Bitcoin, the largest cryptocurrency, impacts herding in the cryptocurrency market. We first estimate Equation (1) for the following three sub-periods: 27/12/2013 – 13/02/2017 (the period before Bitcoin crossed over $1,000 and remained above that threshold since); 14/02/2017 – 16/12/2017 (Bitcoin's price-rally from $1,000 to its peak on December 16th, 2017); and 17/12/2017 – 10/07/2018 (following the ensuing price-collapse of Bitcoin). In addition, we explore whether herding is present in Bitcoin's absence by re-estimating Equation (1) without including Bitcoin's returns in its estimation. Finally, we assess whether our results are subject to size effects by repeating the above estimations using the value-weighted specifications of $R_{m,t}$ and $CSAD_t$.

Table 1 reports summary statistics for $R_{m,t}$ and $CSAD_t$ (equal- and value-weighted) for the full sample period. Overall, equal-weighted statistics are higher than value-weighted ones, more so for $R_{m,t}$ (average value of 0.15% versus 0.09%; variance of 0.21% versus 0.16%) compared to $CSAD_t$ (average value of 6.83% versus 6.82%; variance of 0.06% versus 0.05%). All four time-series are characterized by significant (mostly positive) skewness and leptokurtosis, thus exhibiting substantial departures from normality (something further confirmed by the significant Jarque-Bera test statistics).

3. Empirical Results and Discussion

Results in Table 2, Panel A show that, consistent with our expectations, cryptocurrencies exhibit significant herding, given a significantly negative value (-1.3583) of a_2. The a_2-value reported here is far more negative compared to its equivalent ones reported in studies on international equity markets (see e.g. Economou et al., 2015), suggesting that investors herd more strongly in cryptocurrencies. One possible explanation for this is that the cryptocurrency market – much like the Technology sector in the 1990s - is subject to an overall sentiment of optimistic (considering the promised economic potential of the underlying blockchain technology) uncertainty (as that potential has yet to be fully realized). Therefore, given the ambiguity surrounding the fundamentals of this asset class and the fact that cryptocurrencies are noise-prone (Cheung et al., 2015; Fry and Cheah, 2016), many investors are expected to deem the trades of their peers informative enough and opt for monitoring them, thus promoting herding in the cryptocurrency market.

To assess whether this herding is asymmetric and, hence, which market states contribute to its presence, we test whether it varies with the performance, volatility and trading volume of the cryptocurrency market. Our results denote that cryptocurrency herding exhibits asymmetric properties with respect to all three variables conditioned on. As Panel B in Table 2 shows, both a_3 and a_4 are significantly negative, with a_3 being much larger in absolute value, denoting that herding appears stronger on days when the performance of the cryptocurrency market is positive, on average. Moreover, Panel C in Table 2 shows that herding is present on days with both high and low volatility, with low volatility days entailing stronger herding (a_4 is larger in absolute value compared to a_3); furthermore, Panel D in Table 2 suggests that cryptocurrencies herd on high-volume days only, as the significantly negative a_3-value indicates. Overall, herding appears stronger on days with positive market performance, low volatility and high volume, with the difference between a_3 and a_4 being consistently significant for all three tests (as the F-test statistics in Table 2, Panels B to D denote), thus confirming the significance of the herding asymmetries reported here.

Panels E-G in Table 2 show that herding is significant across all three sub-periods of Bitcoin's price evolution (a_2 is consistently negative and significant), with its magnitude progressively declining (a_2 grows less negative over time). These results suggest that, even though Bitcoin has retained its position as the largest cryptocurrency since its inception, its abrupt up- and down-movements following February 2017 do not appear to be associated with stronger herding in the cryptocurrency market compared to the pre-2017 period. This indicates that cryptocurrency herding is not Bitcoin-bound, something further confirmed by the results in Panel H of Table 2, which show that removing Bitcoin does not lead herding to dissipate; on the contrary, herding is present and stronger compared to the case when Bitcoin was included in the estimations (a_2 is a significant -1.3947 in Panel H compared to its -1.3583 value in Panel

A)[5]. Taken together, the results from Panels E-H demonstrate that Bitcoin's presence and trends over time are not as important determinants for cryptocurrency herding as one might expect, in line with Vidal-Tomás et al. (in press), who found that Bitcoin did not motivate herding among their sample's cryptocurrencies. It is possible that the decreasing herding across the three sub periods reported here is the result of the exponential rise in the number of cryptocurrencies in recent years due to the explosive growth of initial coin offerings; given the limited attention inherent in human cognition (Hirshleifer, 2015), it is reasonable to assume that investors of one cryptocurrency find it less feasible to monitor (and, hence, also copy) investors' trades in other cryptocurrencies as the universe of cryptocurrencies grows. Although focusing on Bitcoin as a benchmark for this market could help investors circumvent this issue, it is more likely that the growth in cryptocurrency-numbers has led Bitcoin's prime position to be challenged (something further confirmed by its gradually decreasing fraction of the total market capitalization as shown on www.coinmarketcap.com).

Table 3 reports our value-weighted herding estimations. As the estimates in Panel A show, herding is insignificant, with similar results reported in Panel H when Bitcoin is excluded. Herding appears on days of positive performance and high volume (Panels B and D; no herding is detected for negative performance and low volume days); herding is present on both high and low volatility days, more strongly so during the latter. All differences between a_3 and a_4 are significant (as the F-test statistics in Table 3, Panels B to D denote), thus confirming that herding asymmetries hold for value-weighted tests. We also find that investors herd during the first two sub-periods (i.e. up to Bitcoin's peak on December 16th, 2017), yet not during the third one (corresponding to Bitcoin's price-collapse). Overall, herding – where significant – appears stronger in equal- compared to value-weighted estimations, as the magnitude of the

[5] Performing an F-test for the difference between the a_2-estimates reported in Panels A and H in Table 2 reveals said difference to be insignificant (F-value is 0.0272 with a p-value of 0.8691), thus indicating that including or excluding Bitcoin from the estimations generates insignificant difference in herding.

significantly negative herding-related coefficients in Table 3 is, in all cases, smaller compared to their equivalent values from the equal-weighted estimations in Table 2. In effect, this suggests that smaller cryptocurrencies help amplify the magnitude of herding, similar to the findings of Vidal-Tomás et al. (in press) who showed that cryptocurrency herding is mainly due to smaller cryptocurrencies herding toward larger ones.

To further investigate the role of size in cryptocurrencies' herding, we sort our sample's cryptocurrencies each year according to their market capitalization as of December 31st of the immediately preceding year, split them into four, equal-sized quartiles (quartile 1 is the smallest; quartile 4 the largest) and estimate Equation (1) for each quartile. Results reported in Table 4 confirm the presence of a size effect in the herding dynamics of this asset class. Herding is significant for quartiles 1 to 3 (a_2 is significantly negative in Panels A - C, dissipating in absolute terms in quartile 3 compared to the other two quartiles), with its significance disappearing in quartile 4, thus again confirming that, although this asset class is dominated by a few large cryptocurrencies, its herding is strongly motivated by their smaller counterparts.

4. Conclusion

Cryptocurrencies constitute an asset class characterized by the absence of fundamentals, substantial volatility, and widespread noise- and sentiment-driven trading. Although these conditions are conducive to herding, its presence in that market has been subject to limited research. Our results show that cryptocurrency herding is significant (irrespective of Bitcoin's presence and trends over time), more strongly so during up-markets, low volatility and high volume days, with smaller cryptocurrencies enhancing its magnitude. Considering the rapid growth of the cryptocurrency market, our findings raise concerns as regards its destabilizing potential, an issue of key relevance to the ongoing debate on the regulatory treatment of this new asset class.

Tables

Table 1: Descriptive statistics

	Equal-weighted		Value-weighted	
	$R_{m,t}$	$CSAD_t$	$R_{m,t}$	$CSAD_t$
Mean	0.0015	0.0683	0.0009	0.0682
Variance	0.0021	0.0006	0.0016	0.0005
Maximum	0.2014	0.2799	0.1723	0.2385
Minimum	-0.2779	0.0177	-0.2411	0.0152
Skewness	-0.7798***	1.7611***	-0.8660***	1.2611***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Excess kurtosis	4.9032***	7.5247***	5.9793***	3.7907***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Jarque-Bera	1827.7595***	4765.6782***	2675.4972***	1431.2898***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: The table reports summary statistics for $R_{m,t}$ and $CSAD_t$ between 27/12/2013 and 10/07/2018. Parentheses include p-values.

Table 2: Herding estimations (equal weighted)

	a_0	a_1	a_2	a_3	a_4	R^2
Panel A: Unconditional herding						
	0.0586***	0.3979***	-1.3583***			0.0997
	(0.0010)	(0.0478)	(0.2423)			
Panel B: Herding conditional on market performance						
	0.0583***	0.5778***	0.2145***	-2.3568***	-0.5099**	0.1383
	(0.0010)	(0.0594)	(0.0454)	(0.4351)	(0.2166)	
F-stat	22.2327***					
(H0: $\alpha_3 = \alpha_4$)	(0.0000)					
Panel C: Herding conditional on market volatility						
	0.0587***	0.4491***	0.4574***	-1.6558***	-4.4887***	0.1076
	(0.0012)	(0.0507)	(0.1201)	(0.2725)	(1.8663)	
F-stat	3.4412*					
(H0: $\alpha_3 = \alpha_4$)	(0.0638)					
Panel D: Herding conditioned on market volume						
	0.0596***	0.4675***	0.2504***	-1.7523***	-0.7376	0.1119
	(0.0010)	(0.0510)	(0.0709)	(0.3010)	(0.5039)	
F-stat	3.4379**					
(H0: $\alpha_3 = \alpha_4$)	(0.0637)					
Panel E: Herding between 27/12/2013 and 13/02/2017						
	0.0566***	0.5789***	-2.0779***			0.1681
	(0.0011)	(0.0576)	(0.2622)			
Panel F: Herding between 14/02/2017 and 16/12/2017						
	0.0574***	0.5343***	-1.7522***			0.2124
	(0.00100)	(0.0542)	(0.3485)			
Panel G: Herding between 17/12/2017 and 10/07/2018						
	0.0573***	0.2844***	-0.8109***			0.0827
	(0.0009)	(0.0524)	(0.2848)			
Panel H: Herding excluding Bitcoin						
	0.0594***	0.4111***	-1.3947***			0.1017
	(0.0010)	(0.0492)	(0.2414)			

Note: This table reports Newey-West consistent estimates from herding estimations using the equal-weighted versions of $R_{m,t}$ and $CSAD_t$. Parentheses include heteroskedasticity and autocorrelation corrected standard errors. The F-test is used to test for the significance of the difference between a_3 and a_4 in Panels B, C and D.

Table 3: Herding estimations (value weighted)

	a_0	a_1	a_2	a_3	a_4	R^2
Panel A: Unconditional herding						
	0.0635^{***}	0.2056^{***}	-0.3102			0.0510
	(0.0010)	(0.0465)	(0.2475)			
Panel B: Herding conditional on market performance						
	0.0632^{***}	0.3155^{***}	0.1212^{**}	-1.1406^{**}	0.1859	0.0583
	(0.0010)	(0.0626)	(0.0516)	(0.58734)	(0.2604)	
F-stat	5.1821^{**}					
(H_0: $\alpha_3 = \alpha_4$)	(0.0228)					
Panel C: Herding conditional on market volatility						
	0.0620^{***}	0.2849^{***}	0.4988^{***}	-0.7111^{***}	-8.1427^{***}	0.0623
	(0.0011)	(0.0495)	(0.1372)	(0.2614)	(2.3769)	
F-stat	10.4963^{***}					
(H_0: $\alpha_3 = \alpha_4$)	(0.0012)					
Panel D: Herding conditioned on market volume						
	0.0652^{***}	0.3496^{***}	-0.1860^{***}	-1.1519^{***}	1.6510^{***}	0.1173
	(0.0010)	(0.0474)	(0.0689)	(0.2798)	(0.5199)	
F-stat	23.3612^{***}					
(H_0: $\alpha_3 = \alpha_4$)	(0.0000)					
Panel E: Herding between 27/12/2013 and 13/02/2017						
	0.0627^{***}	0.2656^{***}	-0.6080^{**}			0.0663
	(0.0011)	(0.0538)	(0.3096)			
Panel F: Herding between 14/02/2017 and 16/12/2017						
	0.0619^{***}	0.4018^{***}	-1.1409^{***}			0.1316
	(0.0011)	(0.0491)	(0.2883)			
Panel G: Herding between 17/12/2017 and 10/07/2018						
	0.0606^{***}	0.1464^{***}	0.1572			0.0653
	(0.0011)	(0.0522)	(0.2503)			
Panel H: Herding excluding Bitcoin						
	0.0638^{***}	0.2390^{***}	0.2450			0.1450
	(0.0013)	(0.0714)	(0.5501)			

Note: This table reports Newey-West consistent estimates from herding estimations using the value-weighted versions of $R_{m,t}$ and $CSAD_t$. Parentheses include heteroskedasticity and autocorrelation corrected standard errors. The F-test is used to test for the significance of the difference between a_3 and a_4 in Panels B, C and D.

Table 4: Herding estimations for size quartiles

	a_0	a_1	a_2	R^2
Panel A: Quartile 1				
	0.0438***	0.9164****	-2.2462****	0.3007
	(0.0018)	(0.0705)	(0.6087)	
Panel B: Quartile 2				
	0.0121***	1.4244***	-3.0448***	0.5616
	(0.0016)	(0.0644)	(0.1915)	
Panel C: Quartile 3				
	0.0194***	0.6178***	-0.9825***	0.2482
	(0.0018)	(0.724)	(0.1049)	
Panel D: Quartile 4				
	0.0232***	0.7349***	-0.4041	0.4604
	(0.0017)	(0.0883)	(0.6266)	

Note: This table reports Newey-West consistent estimates from herding estimations for each of the four size quartiles of cryptocurrencies, using the equal-weighted versions of $R_{m,t}$ and $CSAD_t$ for the estimation of herding in each. Parentheses include heteroskedasticity and autocorrelation corrected standard errors.

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